

Brief Discussion on Scenes and Strategies in Capital Markets Manipulation Detection: From Influence Diffusion Perspectives

Chang Liao

Dongguan Securities Company Limited, China

Abstract. In capital market, earlier detection of the influential entities can be beneficial to both market investors' and regulators' decision making, those whose change can significantly affect the whole trend of the related ones. Meanwhile, market manipulation in capital markets is a serious concern, encompassing tactics like pump and dump, market cornering, spoofing, and wash trading, which disrupt market fairness and erode investor trust. Market manipulation encompasses a range of activities designed to artificially influence the price or trading volume. By leveraging both information behavior data(stock news opinion/volume) and business behavior(stock trading price/volume), together with trade patterns and communication channels, several herding based manipulation scenes and detection models are discussed and proposed.

1 Introduction

Herding is defined to include any behavior similarity/dissimilarity brought about by the interaction of individuals. It is due to the real or imagined pressure from others or groups, a person's behavior or opinion has changed. When this concept is constantly extended and used to describe the social phenomenon of human beings, it can be expressed in many forms mainly refers to social and economic situations in which an individual's decision making is highly influenced or conformed by the decisions of others. Sometimes, people are expected to conform to a kind of expectations or requirements, but do not really believe in what they do - for example, people sometimes wear a tie, although they do not like this - this is a kind of external force and performance, the purpose is to get a reward or avoid punishment, sometimes people really believe that the group does things, because people believe that milk is nutritious - such a sincere, intrinsic conformity known as the "acceptance".

2 General Research Framework on Fake News and Market Manipulation Detection

This discussion attempts to sort out and discuss the application of network and behavioral analysis in areas such as securities issuance, information disclosure, securities investment trading, securities illegal trading, securities market risk supervision, and securities investor protection. It also aims to form typical cases and

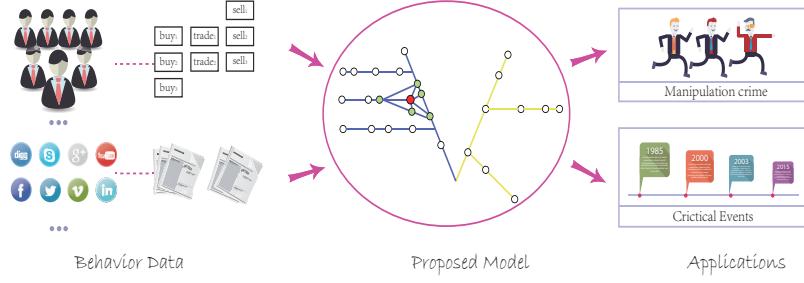


Fig. 1: Overview on Manipulation Detection Framework.

discuss solutions in conjunction with the China Securities Regulatory Commission's (CSRC) Technology.

Contrary to theoretical assumptions, securities market investors are not independent of each other; they have various connections. Investors observe and exchange information with each other, and the interactive feedback affects their decisions, which in turn affects the market. This can also be referred to as an information community formed by the information connections among investors. The study intends to model the propagation characteristics of information in the securities market. On one hand, it analyzes herd behavior from the perspective of coordinated trading and quantifies the risk of contagion it causes. On the other hand, it extracts corresponding propagation characteristics from the information sharing brought about by the information network and designs quantitative investment models for this purpose.

With the development of internet technology, the speed of information dissemination has increased, and its coverage has continuously expanded. The impact of related information on the operation of the A-share market is growing larger. The rapid spread of fake news poses a significant potential hazard to society and individuals, making the early detection of fake news (fake news monitoring) widely valuable. In response to the scarcity of fake news data and the susceptibility of information to manipulation, it aims to research the detection of fake news from the perspective of small-sample learning under network propagation analysis. It compares relevant cases of fake news detection and proposed corresponding policy recommendations, combined with algorithmic experimental design and verification results.

3 Manipulation Detection Scene in Merger and Acquisition Process

In capital market, it is well known that M&As are an important alternative to IPOs as an exit option for high-tech entrepreneurs and early investors. Each year, industry giants spend tens of billions of dollars in acquiring smaller firms for market entrance, strategic intellectual property, and talented employees. Meanwhile, mergers and acquisitions around startups are arranged by venture capitalists to consolidate resources and reduce competitive pressure.

Merger and Acquisition (MA for short in this paper) is a long-lasting process starting from the announcement to the final closure, no mentioning many negotiations started way earlier [15]. Along with this boom, not surprisingly, the media is often full of reports about high-profile M&As involving startups. Nevertheless, to most party except investment banker, the process itself is still more of a black box. The implicit information hidden in statement and news during the MA process is usually ignored in current academic research. The credibility of information source is a difficult problem that is faced by today. For example, how to judge from the site to update the data, stock it, micro-blog and so on the true and false of news, how to reduce the impact of noise on the real information, etc.. Involved in large information sources of noise and a large number of false news, it is difficult to distinguish the authenticity. The position of the information publisher will greatly affect the credibility of the information. Such as information related to the interests of the press release issued will with subjective tendency and guidance, strongly modify negative information and amplify the positive information, these have greatly increased the information to understand and differentiate difficulty [2].

4 Manipulation Detection Scene in Stock Trading Process

Investors are not independent of gathering information, but by the mutual influence. The investors in the market is not necessarily based on their own information and beliefs to make decisions, but will succumb to the public [27, 8]. In the securities market, investors' trading behavior is not independent, it is often affected by the influence of other people around. Moreover, manipulators have constantly devised new techniques to avoid detection. To catch unknown and never-before-seen manipulation, [19] used unsupervised learning to train deep neural networks for detecting stock price manipulation in order to detect unknown and previously unseen manipulation. [4] presents an ensemble model combining supervised and unsupervised deep neural networks to detect stock price manipulation leveraging the accuracy of supervised learning for known patterns and the adaptability of unsupervised learning for novel strategies.

On the complex "rat" behavior monitoring, there are a number of related work. Numerous work [8, 32, 33, 13, 24, 21, 10] have discussed such problems. Graph-based approaches for manipulation detection have been proposed in [25, 11]. From the point of view of trading networks, through the construction of trading networks, from which to find out the close association of abnormal groups, the focus is on the identification and subsequent investigation of suspicious interactions in a network of financial transactions. A pair of individuals that communicate regularly over time should have a stronger relationship, and thus the attributes of the individuals are more likely to exhibit correlation, than a pair of individuals that communicate for a brief time period [30]. In stock market, the core patterns within a sector are representative groups of stocks for the sector when it shows coherent behavior. Such core patterns usually are quasi-cliques. A dense sub graph indicates more interactions between the nodes, which have tight connections. [1] tries to focus on this problem by heuristic methods.

5 Main Ideas on Network Analysis Method

Influence analysis is an important research topic [29, 34, 28]. The main existing problem is that influence interacts with many factors, and how to distinguish is not easy. Tremendous work has been done for influence analysis by diffusion model given the network structure of entities. However, in many social applications, there are not explicit relationship ties declared between entities even if such functionality exists. Thus, how to measure influence in different types of data has been investigated recently, such as latent influence discovering from user adoption behavior data [14], mobile phone data [7], social network [9], trading data [26], blockchain network data [12]. Influence diffusion has attracted considerable attention in social networks [17, 22, 16]. [18] proposes to extract influential nodes based on it. [38] introduces behavioral dynamics as the micro mechanism to describe the dynamic process of a node's neighbors get infected by a cascade after this node get infected (i.e. one-hop subcascades).

When topic is treated as a special kind of community, there are also some similar works [36, 5, 3]. Spatial-temporal events as cohesive anomalies is studied in [37], while overlapping issue is investigated in [39]. Anomalous network structure is sought in the time-sliced network, illustrating the occurrences of unusual behaviour among members [35, 31, 20]. More specifically, supervised tensor regression learning approaches are proposed to investigate the joint impact of different information sources. What's more, social status and social homophily theories, including temporal and structural patterns are to incorporate. Moreover, several work [6, 23] have been proposed to detect misinformation cascades in social networks by analyzing the propagation dynamics and user features within the spread of information.

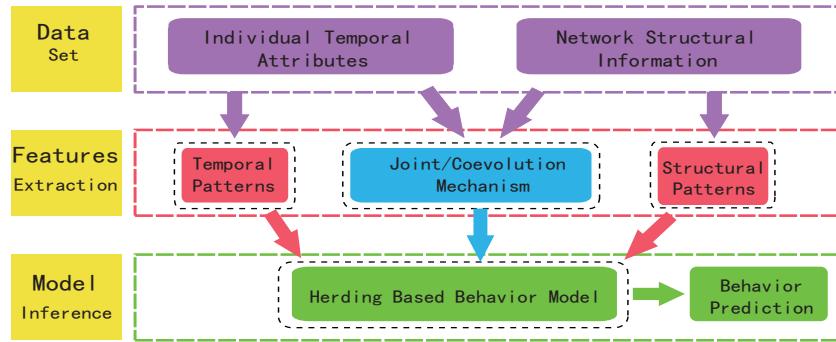


Fig. 2: Interaction Behavior Tracking Framework

References

1. Abello, J., Resende, M.G.C., Sudarsky, S.: Massive quasi-clique detection. In: LATIN 2002: Theoretical Informatics, 5th Latin American Symposium, Cancun, Mexico, April 3-6, 2002, Proceedings (2002)

2. Ahern, K.R., Sosyura, D.: Who writes the news? corporate press releases during merger negotiations. *The Journal of Finance* 69(1), 241–291 (2014)
3. Althoff, T., Dong, X.L., Murphy, K., Alai, S., Dang, V., Zhang, W.: Timemachine: Timeline generation for knowledge-base entities. In: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 19–28. ACM (2015)
4. Chullamonthon, P., Tangamchit, P.: Ensemble of supervised and unsupervised deep neural networks for stock price manipulation detection. *Expert Systems with Applications* 220, 119698 (2023)
5. Deng, Z.H., Gong, X., Jiang, F., Tsang, I.W.: Effectively predicting whether and when a topic will become prevalent in a social network (2015)
6. Ducci, F., Kraus, M., Feuerriegel, S.: Cascade-lstm: A tree-structured neural classifier for detecting misinformation cascades. In: proceedings of the 26th ACM SIGKDD international conference on Knowledge Discovery & Data Mining. pp. 2666–2676 (2020)
7. Eagle, N., Pentland, A.S., Lazer, D.: Inferring friendship network structure by using mobile phone data. *Proceedings of the national academy of sciences* 106(36), 15274–15278 (2009)
8. Fakhraei, S., Foulds, J., Shashanka, M., Getoor, L.: Collective spammer detection in evolving multi-relational social networks. In: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 1769–1778. ACM (2015)
9. Goyal, A., Bonchi, F., Lakshmanan, L.V.: Learning influence probabilities in social networks. In: Proceedings of the third ACM international conference on Web search and data mining. pp. 241–250. ACM (2010)
10. Hameed, A., Titman, S., Wei, J.Z., Zhang, H.: Information transmission in stock and bond markets. Available at SSRN 4728568 (2024)
11. Haque, M.Z., Hossain, M.S., Lucky, S.A.: Impact of social networking sites (snss) on stock market: Review, synthesis and direction for future research. *International Journal of Financial Engineering* p. 2331001 (2024)
12. Hassan, M.U., Rehmani, M.H., Chen, J.: Anomaly detection in blockchain networks: A comprehensive survey. *IEEE Communications Surveys & Tutorials* 25(1), 289–318 (2022)
13. Hooi, B., Shah, N., Beutel, A., Gunneman, S., Akoglu, L., Kumar, M., Makhija, D., Faloutsos, C.: Birdnest: Bayesian inference for ratings-fraud detection. *arXiv preprint arXiv:1511.06030* (2015)
14. Iwata, T., Shah, A., Ghahramani, Z.: Discovering latent influence in online social activities via shared cascade poisson processes. In: Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (2013)
15. John, K., Qi, Q., Wang, J.: Bank integration and the market for corporate control: Evidence from cross-state acquisitions. *Management Science* 66(7), 3277–3294 (2020)
16. Juul, J.L., Ugander, J.: Comparing information diffusion mechanisms by matching on cascade size. *Proceedings of the National Academy of Sciences* 118(46), e2100786118 (2021)
17. Kempe, D., Kleinberg, J., Tardos, E.: Maximizing the spread of influence through a social network. *Theory of Computing* 137–146(4) (2003)
18. Kimura, M., Saito, K., Nakano, R.: Extracting influential nodes for information diffusion on a social network. In: National Conference on Artificial Intelligence (2007)
19. Leangarun, T., Tangamchit, P., Thajchayapong, S.: Stock price manipulation detection using deep unsupervised learning: The case of thailand. *IEEE Access* 9, 106824–106838 (2021)
20. Li, Q., Jiang, L., Li, P., Chen, H.: Tensor-based learning for predicting stock movements. In: National Conference on Artificial Intelligence (2015)
21. Liu, A.Z., Xu, S., Zhang, X.M., Zhao, X.: Can investors benefit from the wisdom of crowds? evidence from wikipedia and insider trading. *Social Science Electronic Publishing*

22. Luo, Y., Xiao, Y., Cheng, L., Peng, G., Yao, D.: Deep learning-based anomaly detection in cyber-physical systems: Progress and opportunities. *ACM Computing Surveys (CSUR)* **54**(5), 1–36 (2021)
23. Ma, J., Wan, M., Yang, L., Li, J., Hecht, B., Teevan, J.: Learning causal effects on hypergraphs. In: *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. pp. 1202–1212 (2022)
24. Mehran, R., Oyama, A., Shah, M.: Abnormal crowd behavior detection using social force model. In: *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on* pp. 935–942. IEEE (2009)
25. Rahmani, A., Afra, S., Zarour, O., Addam, O., Koochakzadeh, N., Kianmehr, K., Alhajj, R., Rokne, J.: Graph-based approach for outlier detection in sequential data and its application on stock market and weather data. *Knowledge-Based Systems* **61**, 89–97 (2014)
26. Ravina, E., Sapienza, P.: What do independent directors know? evidence from their trading. *Review of Financial Studies* **23**(3), 962–1003 (2010)
27. Redmond, U., Harrigan, M., Cunningham, P.: Mining dense structures to uncover anomalous behaviour in financial network data. In: *Modeling and mining ubiquitous social media*, pp. 60–76. Springer (2012)
28. Shahaf, D., Guestrin, C., Horvitz, E.: Metro maps of science. In: *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*. pp. 1122–1130. ACM (2012)
29. Shaparenko, B., Joachims, T.: Information genealogy: uncovering the flow of ideas in non-hyperlinked document databases. In: *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining*. pp. 619–628. ACM (2007)
30. Sharma, K., Zhang, Y., Ferrara, E., Liu, Y.: Identifying coordinated accounts on social media through hidden influence and group behaviours. In: *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. pp. 1441–1451 (2021)
31. Shi, X., Paiement, J.F., Grangier, D., Yu, P.S.: Learning from heterogeneous sources via gradient boosting consensus. In: *SIAM International Conference on Data Mining* (2012)
32. Song, Y., Cao, L.: Graph-based coupled behavior analysis: A case study on detecting collaborative manipulations in stock markets. In: *The 2012 International Joint Conference on Neural Networks (IJCNN)*. pp. 1–8. IEEE (2012)
33. Tian, T., Zhu, J., Xia, F., Zhuang, X., Zhang, T.: Crowd fraud detection in internet advertising. In: *Proceedings of the 24th International Conference on World Wide Web*. pp. 1100–1110. International World Wide Web Conferences Steering Committee (2015)
34. Wang, T., Wang, D., Wang, F.: Quantifying herding effects in crowd wisdom. In: *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*. pp. 1087–1096. ACM (2014)
35. Xie, S., Hu, Q., Zhang, J., Gao, J., Fan, W., Yu, P.S.: Robust crowd bias correction via dual knowledge transfer from multiple overlapping sources. In: *Big Data (Big Data), 2015 IEEE International Conference on*. pp. 815–820. IEEE (2015)
36. Yan, X., Guo, J., Lan, Y., Xu, J., Cheng, X.: A probabilistic model for bursty topic discovery in microblogs. In: *Twenty-ninth Aaai Conference on Artificial Intelligence* (2015)
37. Yang, N., Kong, X., Wang, F., Philip, S.Y.: When and where: Predicting human movements based on social spatial-temporal events. In: *SDM*. pp. 515–523. SIAM (2014)
38. Yu, L., Cui, P., Wang, F., Song, C.: From micro to macro: Uncovering and predicting information cascading process with behavioral dynamics pp. 559–568 (2015)
39. Zhang, Y., Levina, E., Zhu, J.: Detecting overlapping communities in networks using spectral methods. *arXiv preprint arXiv:1412.3432* (2014)